# 6.S891 Lecture 17: Spectral Independence from Zero-Freeness 

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November 9, 2023

In this lecture, we return to (multivariate) zero-freeness of the partition function. We show that it implies spectral independence and hence, fast mixing of Glauber dynamics.

## 1 The Generating Polynomial and its Zero-Freeness

Let $\mu$ be a probability distribution over $2^{[n]}$ (which of course can be identified with $\{ \pm 1\}^{n}$ ). Define its generating polynomial as

$$
\begin{equation*}
g_{\mu}(\boldsymbol{z}) \stackrel{\text { def }}{=} \sum_{S \subseteq[n]} \mu(S) \cdot \boldsymbol{z}^{S}, \tag{1}
\end{equation*}
$$

where we use the shorthand $\boldsymbol{z}^{S} \stackrel{\text { def }}{=} \prod_{i \in S} z_{i}$. This is a multiaffine polynomial of degree (at most) $n$. Its logarithm is essentially the cumulant generating function $\mathcal{L}_{\mu}$ of $\mu$ we previously saw, except with a change of variables to obtain a polynomial. One of the central ideas in the study of the geometry of polynomials is the following.

Theme 1.1. It is fruitful to relate the analytic/algebraic properties of $g_{\mu}$ to the probabilistic/combinatorial properties of $\mu$ itself.

For instance, a consequence of Barvinok's algorithm is that whenever $g_{\mu}$ admits a large zero-free region, then we have efficient algorithms for estimating $g_{\mu} .{ }^{1}$ In this lecture, we will be interested in deducing correlation bounds given zero-freeness of $g_{\mu}$. The following beautiful theorem, which we will not prove, is an example of such a result.

Theorem 1.2 ([BBL09]). Suppose $g_{\mu}$ is real stable, i.e. that $g_{\mu} \neq 0$ whenever $\operatorname{Im} z_{i}>0$ for all $i \in[n]$. Then $\mu$ is negatively correlated in the sense that

$$
\operatorname{Pr}_{S \sim \mu}[j \in S \mid i \in S] \leq \operatorname{Pr}_{S \sim \mu}[j \in S \mid i \notin S], \quad \forall i \neq j
$$

Real stability of the generating polynomial of $\mu$ is sometimes referred to as the strongly Rayleigh property. It turns out to be an extremely robust notion of negative correlation, one which has found many applications; see e.g. [Pem12] and references therein. We also previously saw that negatively correlated distributions on (homogeneous) set systems are 1 -spectrally independent. The main result of this lecture is to establish a more direct connection between zero-freeness and spectral independence, one which does not require zero-freeness w.r.t. an entire half-plane.

Recall the following notion of multivariate zero-freeness we used previously.
Definition 1 (Stability). Let $\Gamma_{1}, \ldots, \Gamma_{n} \subseteq \mathbb{C}$ be subsets of the complex plane. We say a multivariate polynomial $p\left(z_{1}, \ldots, z_{n}\right)$ is $\Gamma_{1} \times \cdots \times \Gamma_{n}$-stable if $p(\boldsymbol{z}) \neq 0$ whenever $z_{i} \in \Gamma_{i}$ for all $i=1, \ldots, n$. If $\Gamma_{1}=\cdots=\Gamma_{n}=\Gamma$ for some $\Gamma \subseteq \mathbb{C}$, then we simply say $p$ is $\Gamma$-stable.

Theorem 1.3 ([CLV21]; building on $[\mathrm{Ali}+21])$. Suppose there exists a constant $\delta>0$ such that $g_{\mu}$ is stable w.r.t. the open radius- $\delta$ disk $\mathbb{D}(1, \delta)$ around 1 . If in addition the marginals of $\mu$ are bounded

[^0]in the sense that there is a constant $0<\mathscr{B} \leq 1 / 2$ such that $\operatorname{Pr}_{S \sim \mu}[i \in S], \operatorname{Pr}_{S \sim \mu}[i \notin S] \geq \mathscr{B}$ for all $i \in[n]$, then
$$
\sum_{j=1}^{n}\left|\Psi_{\mu}(i \rightarrow j)\right| \leq \frac{4}{\mathscr{B}(1-\mathscr{B}) \delta^{2}}, \quad \forall i \in[n]
$$

In particular, $\mu$ is $O\left(1 / \mathscr{B} \delta^{2}\right)$-spectrally independent.
Remark 1. The point $\mathbf{1}$ for zero-freeness isn't special. One could look at stability w.r.t. an open radius- $\delta$ disk around any other point $\boldsymbol{\lambda} \in \mathbb{R}_{\geq 0}^{n}$, in which case we'd get spectral independence for the tilted distribution $\mu_{\boldsymbol{\lambda}}(S) \propto \mu(S) \cdot \boldsymbol{\lambda}^{S}$.

Theorem 1.4 ([Ali +21$])$. Suppose there exists a constant $\alpha>0$ such that $g_{\mu}$ is stable w.r.t. the sector

$$
\begin{equation*}
S_{\alpha} \stackrel{\text { def }}{=}\left\{r e^{i \theta}:|\theta|<\alpha \pi / 2, r>0\right\} . \tag{2}
\end{equation*}
$$

around the nonnegative real axis with aperture $\alpha \pi$. Then

$$
\sum_{j=1}^{n}\left|\operatorname{Pr}_{S \sim \mu}[j \in S \mid i \in S]-\operatorname{Pr}_{S \sim \mu}[j \in S \mid i \notin S]\right| \leq \frac{2}{\alpha}, \quad \forall i \in[n]
$$

and $\mu$ is $\left(\frac{2}{\alpha}-1\right)$-spectrally independent. Furthermore, the same inequality holds for all exponential tilts of $\mu$, i.e. distributions of the form $\mu_{\boldsymbol{\lambda}}(S) \propto \mu(S) \cdot \boldsymbol{\lambda}^{S}$ for some $\boldsymbol{\lambda} \in \mathbb{R}_{\geq 0}^{n}$.

Remark 2. In the special case $\alpha=1, S_{\alpha}$ becomes the open right half-plane $\{z \in \mathbb{C}: \operatorname{Re} z>0\}$. Polynomials which are stable w.r.t. $S_{1}$ are often called Hurwitz stable.

The rough intuition behind these statements is the following: Since the correlations of $\mu$ are given by second-order derivatives of $\log g_{\mu}$ at $\mathbf{1}$, these correlations are small if $\log g_{\mu}(\mathbf{1})$ is "smooth" in some sense. This is only the case if $\mathbf{1}$ is far away from the zeros of $g_{\mu}$. For more results accommodating more general zero-free regions, see [Ali +21 ; CLV21].

### 1.1 Applications

Before we prove Theorems 1.3 and 1.4, let us mention a few applications.
Example 1 (Hardcore Model in Tree Uniqueness). We previously mentioned that Peters-Regts [PR19] established stability of the multivariate independence polynomial $Z_{G}(\boldsymbol{\lambda})$ of a graph of maximum degree $\Delta$ in a neighborhood of the interval $\left[0, \lambda_{c}(\Delta)\right)$, where $\lambda_{c}(\Delta)$ is again the uniqueness threshold w.r.t. the infinite $\Delta$-regular tree. In this regime, Barvinok's algorithm furnishes an FPTAS. Combining this zero-freeness result with Theorem 1.3 yields an alternative proof of $O$ (1)-spectral independence of the hardcore Gibbs measure in the uniqueness regime, albeit with worse quantitative bounds.
Example 2 (Monomer-Dimer Model). Recall we previously showed that the univariate matching polynomial $\mathcal{M}_{G}(z)=\sum_{M \subseteq E \text { matching }} z^{|M|}$ real-rooted. This is the Heilmann-Lieb Theorem [HL72], and more in depth analysis reveals that for every nonnegative vector of edge weights $\boldsymbol{\lambda} \in \mathbb{R}_{\geq 0}^{E}$, the multivariate (vertex) matching polynomial

$$
\mathcal{M}_{G}(\boldsymbol{z}) \stackrel{\text { def }}{=} \sum_{\substack{M \subseteq E \\ \text { matching }}} \prod_{e \in M} \lambda_{e} \prod_{v \text { unmatched }} z_{v}
$$

is Hurwitz stable; see e.g. [BB09]. Combined with Theorem 1.4, this in particular implies that for any graph $G=(V, E)$, the monomer-dimer Gibbs distribution satisfies the correlation bounds

Note that no assumptions on the degree were made. This result was first proved in a paper of Jeff Kahn [Kah00] using a simple but clever inductive argument.

There are also additional applications of this method to determinantal point processes, even subgraphs, edge covers, edge spin systems (i.e. spin systems on line graphs), etc. [Ali +21 ; CLV21].

## 2 A Little Complex Analysis

To formalize the above intuition, we will leverage the following standard fact from complex analysis, which captures the "rigidity" of smooth complex functions.

Lemma 2.1 (Schwarz-Pick). Let $f: \mathbb{D}(0,1) \rightarrow \mathbb{D}(0,1)$ is a univariate holomorphic function. Then $\left|f^{\prime}(0)\right| \leq 1-|f(0)|^{2} \leq 1$.

In light of the Schwarz-Pick lemma, our strategy will be to construct such a univariate holomorphic function $f$ such that $f$ maps $\mathbb{D}(0,1)$ into itself, and $\left|f^{\prime}(0)\right| \approx \sum_{j=1}^{n}\left|\Psi_{\mu}(i \rightarrow j)\right|$, perhaps up to constants depending on $\mathscr{B}, \delta$.

Proof of Theorem 1.3. Fix an arbitrary $i \in[n]$, and define

$$
F_{i}(\boldsymbol{z}) \stackrel{\text { def }}{=} \frac{\partial_{z_{i}} \log g_{\mu}(\boldsymbol{z})}{\operatorname{Pr}_{S \sim \mu}[i \in S] \cdot \operatorname{Pr}_{S \sim \mu}[i \notin S]}
$$

Note that $\partial_{z_{j}} F_{i}(\mathbf{1})=\Psi_{\mu}(i \rightarrow j)$ for all $j \in[n]$. Our goal is to construct appropriate maps $\psi: \mathbb{C} \rightarrow$ $\mathbb{C}$ and $\varphi: \mathbb{C} \rightarrow \mathbb{C}^{n}$ such that the composition $f(z)=\psi\left(F_{i}\left(\varphi_{1}(z), \ldots, \varphi_{n}(z)\right)\right)$ is holomorphic and satisfies $f(\mathbb{D}(0,1)) \subseteq \mathbb{D}(0,1)$. If we have such $\psi, \boldsymbol{\varphi}$, then by applying the Schwarz-Pick Lemma,

$$
\begin{align*}
1 & \geq\left|f^{\prime}(0)\right|  \tag{Lemma2.1}\\
& =\left|\psi^{\prime}\left(F_{i}(\boldsymbol{\varphi}(0))\right)\right| \cdot\left\langle\nabla F_{i}(\boldsymbol{\varphi}(0)), \boldsymbol{\varphi}^{\prime}(0)\right\rangle \\
& =\left|\psi^{\prime}\left(F_{i}(\boldsymbol{\varphi}(0))\right)\right| \cdot \sum_{j=1}^{n} \Psi_{\mu}(i \rightarrow j) \cdot \varphi_{j}^{\prime}(0) .
\end{align*}
$$

(Chain Rule)

A natural and simple choice is to take $\psi, \varphi$ to be affine functions.

- To ensure that $f$ is holomorphic, we use $\varphi$ to map $\mathbb{D}(0,1)$ into the region of stability of $g_{\mu}$, which we assumed is $\mathbb{D}(1, \delta)$. For convenience, let us allow an epsilon of room. Let

$$
\varphi_{j}(z) \stackrel{\text { def }}{=} 1+\frac{\delta}{2} s_{j} z,
$$

where $s_{j}=\operatorname{sign}\left(\Psi_{\mu}(i \rightarrow j)\right)$. This ensures that $\varphi_{j}(\mathbb{D}(0,1)) \subseteq \mathbb{D}(1, \delta / 2)$ for all $j \in[n]$,

$$
\sum_{j=1}^{n} \Psi_{\mu}(i \rightarrow j) \cdot \varphi_{j}^{\prime}(0)=\frac{\delta}{2} \cdot \sum_{j=1}^{n}\left|\Psi_{\mu}(i \rightarrow j)\right|
$$

In particular, this choice for $\varphi$ alone already implies

$$
\begin{equation*}
\sum_{j=1}^{n}\left|\Psi_{\mu}(i \rightarrow j)\right| \leq \frac{2}{\delta \cdot\left|\psi^{\prime}\left(F_{i}(\mathbf{1})\right)\right|} \tag{4}
\end{equation*}
$$

- Now, we design $\psi$. In order to apply the Schwarz-Pick Lemma, we need $\psi$ to map the image of $\mathbb{D}(0,1)$ under $F_{i} \circ \varphi$ back into $\mathbb{D}(0,1)$. This is the tricky part, since we must understand the image of $F_{i}$. This is also where it is convenient to have an epsilon of room from the definition of $\varphi$, since we only need to consider $F_{i}(\mathbb{D}(1, \delta / 2))$ instead of $F_{i}(\mathbb{D}(1, \delta))$.
Claim 2.2. The image of $\mathbb{D}(1, \delta / 2)$ under $F_{i}$ is contained in $\mathbb{D}\left(0, \frac{2}{\mathscr{B}(1-\mathscr{B}) \delta}\right)$.
Once we have this, an obvious choice for $\psi$ is to scale everything down by a factor of $\frac{\mathscr{B}(1-\mathscr{B}) \delta}{2}$. In particular, we let $\psi(z)=\frac{\mathscr{B}(1-\mathscr{B}) \delta}{2} z$. Plugging this into Eq. (4) immediately implies the theorem. All that remains is to justify Claim 2.2.

Proof of Claim 2.2. Since we assumed the marginal bound $\operatorname{Pr}_{S \sim \mu}[i \in S] \geq \mathscr{B}$, the claim is equivalent to showing that the image of $\mathbb{D}(1, \delta / 2)$ under $\boldsymbol{z} \mapsto \partial_{i} \log g_{\mu}(\boldsymbol{z})$ is contained in $\mathbb{D}(0,2 / \delta)$.

We go by contradiction, making crucial use linearity of $g_{\mu}$ in each of its variables. Fix $z_{1}, \ldots, z_{n} \in \mathbb{D}(1, \delta / 2)$, and write $y=\partial_{i} \log g_{\mu}(\boldsymbol{z})$. We wish to show that $|y|<2 / \delta$. Since

$$
y=\partial_{i} \log g_{\mu}(\boldsymbol{z})=\frac{\partial_{i} g_{\mu}(\boldsymbol{z})}{g_{\mu}(\boldsymbol{z})},
$$

rearranging yields

$$
\begin{equation*}
g_{\mu}(\boldsymbol{z})-\frac{1}{y} \cdot \partial_{i} g_{\mu}(\boldsymbol{z})=0 \tag{5}
\end{equation*}
$$

Suppose for contradiction that $|y| \geq \frac{2}{\delta}$. Then $\left|-\frac{1}{y}\right| \leq \frac{\delta}{2}$. We use this and Eq. (5) to construct a new vector $\boldsymbol{z}^{\prime} \in \mathbb{D}(1, \delta)^{n}$ such that $g_{\mu}\left(\boldsymbol{z}^{\prime}\right)=0$, contradicting $\mathbb{D}(1, \delta)$-stability of $g_{\mu}$.

Define $\boldsymbol{z}^{\prime}$ by $z_{j}^{\prime}=z_{j}$ for all $j \neq i$, and $z_{i}^{\prime}=z_{i}-\frac{1}{y}$. Since $\left|z_{i}-1\right|<\frac{\delta}{2}$ and $\left|-\frac{1}{y}\right| \leq \frac{\delta}{2}$, we have $z^{\prime} \in \mathbb{D}(1, \delta)^{n}$. Furthermore, since $g_{\mu}$ is linear in each of its variables,

$$
\begin{align*}
g_{\mu}\left(\boldsymbol{z}^{\prime}\right) & =\underbrace{\left(g_{\mu}(\boldsymbol{z})-z_{i} \cdot \partial_{i} g_{\mu}(\boldsymbol{z})\right)}_{\text {Monomials without } i}+\underbrace{\left(z_{i}-\frac{1}{y}\right) \cdot \partial_{i} g_{\mu}(\boldsymbol{z})}_{\text {Monomials with } i} \\
& =g_{\mu}(\boldsymbol{z})-\frac{1}{y} \cdot \partial_{i} g_{\mu}(\boldsymbol{z}) \\
& =0 \tag{5}
\end{align*}
$$

## 3 Better Maps for Sectors

If we impose more structure on our zero-free regions, then we can construct much better $\psi, \boldsymbol{\varphi}$ and prove better bounds. We just need to understand where how the map $y \mapsto-\frac{1}{y}$ changes our zero-free region, and how to map between these regions and the unit disk $\mathbb{D}(0,1)$.

Proof of Theorem 1.4. Since $\mu$ and $\mu_{\boldsymbol{\lambda}}$ have the same generating polynomials up to rescaling the variables by nonnegative coefficients, sector stability also holds for $g_{\mu_{\lambda}}$. Hence, without loss of generality, we just prove spectral independence for $\mu$ itself.

Fix an arbitrary $i \in[n]$, and define ${ }^{2}$

$$
F_{i}(\boldsymbol{z})=\log \left(\frac{\partial_{i} g_{\mu}(\boldsymbol{z})}{\left(1-z_{i} \partial_{i}\right) g_{\mu}(\boldsymbol{z})}\right) .
$$

A direct calculation reveals that $\partial_{z_{j}} F_{i}(\mathbf{1})=\operatorname{Pr}_{S \sim \mu}[j \in S \mid i \in S]-\operatorname{Pr}_{S \sim \mu}[j \in S \mid i \notin S]$ for all $j \in[n]$. We construct appropriate maps $\psi: \mathbb{C} \rightarrow \mathbb{C}$ and $\varphi: \mathbb{C} \rightarrow \mathbb{C}^{n}$ such that the composition $f(z)=\psi\left(F_{i}\left(\varphi_{1}(z), \ldots, \varphi_{n}(z)\right)\right)$ satisfies the assumptions of the Schwarz-Pick Lemma, since then we'd have

$$
\begin{equation*}
1-|f(0)|^{2} \geq\left|f^{\prime}(0)\right|=\left|\psi^{\prime}\left(F_{i}(\varphi(0))\right)\right| \cdot \sum_{j \neq i} \Psi_{\mu}(i \rightarrow j) \cdot \varphi_{j}^{\prime}(0) . \tag{6}
\end{equation*}
$$

- Since $g_{\mu}$ is stable w.r.t. the sector $S_{\alpha}$, we use Möbius transformations and exponential maps instead of affine functions. More specifically, take

$$
\begin{align*}
& \qquad \varphi_{j}(z) \stackrel{\text { def }}{=} g\left(s_{j} z\right)^{\alpha}=\left(\frac{1+s_{j} z}{1-s_{j} z}\right)^{\alpha}  \tag{7}\\
& \text { where } \quad g(x)=\frac{1+x}{1-x} \quad \text { and } \quad s_{j}=\operatorname{sign}\left(\Psi_{\mu}(i \rightarrow j)\right), \quad \forall j \in[n] .
\end{align*}
$$

The point is that $\varphi_{j}(\mathbb{D}(0,1)) \subseteq S_{\alpha}$ since the inner Möbius function $g$ maps $\mathbb{D}(0,1)$ to the right half-plane $S_{1}$, and then taking the $\alpha$ th power scales down the angle. A quick calculation

[^1]reveals that $\varphi_{j}^{\prime}(z)=2 s_{j} \alpha \cdot\left(\frac{1+s_{j} z}{1-s_{j} z}\right)^{\alpha-1} \cdot \frac{1}{\left(1-s_{j} z\right)^{2}}$ and so plugging this into Eq. (6) and using $\varphi(0)=1$ gives
\[

$$
\begin{equation*}
\sum_{j \neq i}\left|\Psi_{\mu}(i \rightarrow j)\right| \leq \frac{1}{2 \alpha} \cdot \frac{1-\psi^{\prime}\left(F_{i}(\mathbf{1})\right)^{2}}{\left|\psi^{\prime}\left(F_{i}(\mathbf{1})\right)\right|} \tag{8}
\end{equation*}
$$

\]

- Now let us argue about the image of $F_{i}$, which will then tell us how to construct $\psi$.

Claim 3.1. For every $z_{1}, \ldots, z_{n} \in S_{\alpha}$, we have that

$$
\frac{\partial_{i} g_{\mu}(\boldsymbol{z})}{\left(1-z_{i} \partial_{i}\right) g_{\mu}(\boldsymbol{z})} \notin-S_{\alpha} .
$$

In particular, the image of $S_{\alpha}$ under $F_{i}$ is contained within the strip

$$
\begin{equation*}
\left\{z \in \mathbb{C}:|\operatorname{Im} z|<\left(1-\frac{\alpha}{2}\right) \pi\right\} . \tag{9}
\end{equation*}
$$

Before we prove this claim, let us finish the proof by constructing $\psi$. Let

$$
\psi(z)=g^{-1}\left(\exp \left(\frac{1 / 2}{1-\alpha / 2} \cdot z\right)\right)
$$

where $g^{-1}(z)=\frac{z-1}{z+1}$ is the inverse of the Möbius transformation $g$ we used in the definition of $\varphi$ above. The point is that the inner exponential maps the strip in Claim 3.1 to the right half-plane $S_{1}$, and then $g^{-1}$ maps this right half-plane to $\mathbb{D}(0,1)$. Another quick calculation reveals that

$$
\psi^{\prime}(z)=\frac{2 \exp \left(\frac{1 / 2}{1-\alpha / 2} \cdot z\right)}{\left(1+\exp \left(\frac{1 / 2}{1-\alpha / 2} \cdot z\right)\right)^{2}} \cdot \frac{1 / 2}{1-\alpha / 2}=\frac{1 / 2}{1-\alpha / 2} \cdot \frac{1}{2}\left(1-\psi(z)^{2}\right)
$$

Combined with Eq. (8) yields

$$
\sum_{j \neq i}\left|\Psi_{\mu}(i \rightarrow j)\right| \leq \frac{2}{\alpha}-1
$$

Adding back $\Psi_{\mu}(i \rightarrow i)=1$ to both sides concludes the proof.

Proof of Claim 3.1. Since the image of $-S_{\alpha}$ under the exponential map $z \mapsto \exp (z)$ is the strip in Eq. (9), the first claim indeed implies the second. Let $y=\frac{\partial_{i} g_{\mu}(\boldsymbol{z})}{\left(1-z_{i} \partial_{i}\right) g_{\mu}(\boldsymbol{z})}$ and suppose for contradiction that $y \in S_{-\alpha}$. Then $-\frac{1}{y} \in S_{\alpha}$, whence

$$
\begin{aligned}
0 & =\left(1-z_{i} \partial_{i}\right) g_{\mu}(\boldsymbol{z})-\frac{1}{y} \cdot \partial_{i} g_{\mu}(\boldsymbol{z}) & \quad \text { (Rearranging) } \\
& =g_{\mu}\left(-\frac{1}{y}, \boldsymbol{z}_{-i}\right) . & \left(g_{\mu} \text { is multiaffine }\right)
\end{aligned}
$$

This contradicts $S_{\alpha}$-stability of $g_{\mu}$.

## References

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[^0]:    ${ }^{1}$ This is not entirely true, since Barvinok's algorithm also requires that that zero-free region contains a point at which computing $g_{\mu}$ is easy. For instance, we do not have FPTAS for estimating arbitrary real stable polynomials.

[^1]:    ${ }^{2}$ If the numerator inside the logarithm were multiplied by $z_{i}$, and if $\boldsymbol{z} \in \mathbb{R}_{\geq 0}^{n}$, then we'd exactly have the marginal ratio of $i$ under the tilted measure $\mu_{\boldsymbol{z}}$.

